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Neurocomputing fundamental climate analysis

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Abstract
Rainfall is a natural phenomenon that needs to be studied more deeply and interesting to be analyzed. It involves numbers of human activities such as aviation, agriculture, fisheries, and also disaster risk reduction. Moreover, the characteristics of rainfall data follows seasonality, fluctuation, not normally distributed and it makes traditional time series challenging to use. Therefore, neurocomputing model can be used as an alternative to extraction information from rainfall data and give high performance also accuracy. In this paper, we give short preview about SST Anomalies in Manado, Northern Sulawesi and at the same time comparing the performance of rainfall forecasting by using three types of neurocomputing methods such as Generalized Regression Neural Network (GRNN), Feed forward Neural Network (FFNN), and Localized Multi Kernel Support Vector Regression (LMKSVR). In a nutshell, all of neurocomputing methods give highly accurate forecasting as well as reach low MAPE FFNN 1.65%, GRNN 2.65% and LMKSVR 0.28%, respectively.

Keywords: *GRNN, LMKL SVR, rainfall, soft computing*

1. Introduction

Prediction of daily, monthly rainfall information is essential and needed in various sectors [1, 2].Sometimes, rainfall is difficult to predict accurately due to the dynamic precipitation and complex physical processes involved. Rainfall is one crucial element of weather because it is the primary source of water for life. Rainfall is very closely related to the various sectors of human activities such as agriculture, forestry, fisheries, or even in ecological and biodiversity [3-5] El Niño begins with rainy season withdrawal and the beginning of the dry season forward and the length of the rainy season occurs shorter while the dry season is more extended. La Niña begins with the rainy season happening faster and the beginning of the dry season backward and the length of the rainy season occurs longer term shorter dry season [6, 7]. However, Statistics has an essential role in explaining the phenomenon and information on the problems that exist around. In the heart of statistical environment, numbers of techniques has been used in climatology analysis, especially in the field of neurocomputing application of forecasting, regression, classification and also cluster. Neurocomputing is considered important because data can be extracted as information to decision making. The determination of the beginning of the season and the length of the season is based on Indonesian Agency for Meteorological, Climatological and Geophysics (BMKG) by taking only the parameters of the amount of 10 days rainfall as a consideration. The length of the rainy season is calculated from the first 10 days of the rainy season before the beginning of the dry season. The long dry season is calculated from the first 10 days of the dry season before the start of the rainy season.

2. Research Method

The concept of neurocomputing is far-reaching. In this paper, we only perform neurocomputing simulation by using feedforward neural network, general regression neural network, and localized multi-kernel support vector regression.

2.1. Feed Forward Neural Network

Artificial Neural Network (ANN), or more commonly known as Neural Network (NN), is an information processing system which has characteristics similar to a biological neural network [8-9] ANN is a machine designed for modeling the way the human brain works in doing specific functions or tasks. FFNN is a specific form of Multi-Layer Perceptron (MLP) with one hidden layer. The typical form of FFNN model is written in the following equation:

$$X_t = \psi_o\{ w_{bo} + \sum_{j=1}^{H} w_{jo}\ \psi_j\ (w_{bj} + \sum_{i=1}^{p} w_{ij}\ X_{t-i})\} \tag{1}$$

with
  ψ_o : The activation function used in output layer
  ψ_j : The activation function used in hidden layer
  w_{ij} : The weight of neuron i in input layer to neuron j in hidden layer
  w_{bj} : The bias weight in input layer to neuron j in hidden layer
  w_{jo} : The weight of neuron j in hidden layer to output layer
  w_{bo} : The bias weight in hidden layer to output layer

2.2. Localized Support Vector Regression

Support Vector Regression (SVR) [10-11] is the development of SVM for regression cases [12]. The purpose of SVR is to find a function $f(x)$ as a hyperplane in the form of a regression function which corresponds to all input data with an error ε and makes ε as thin as possible [13]. Suppose there are l training data,(x_i, y_i), $i = 1,..,l$ l where x_i is the input vector $x = \{x_1, x_2, ... x_n\} \subseteq \Re^n$ and the scalar output $y = \{y_i, ... y_l\} \subseteq \Re$ and l are the number of training data. However, we want to determine a function $f(x)$ having the largest deviation ε from the actual target y_i for all training data. If the value of ε is equal to 0 then a perfect regression equation is obtained. The purpose of SVR is to map the vector inputs into the higher dimensions [14]. Suppose a function follows the regression line as the optimal hyperplane[10]:

$$f(x) = w^T \varphi(x) + b \tag{2}$$

with
w = weighted vector
$\varphi(x)$ = Function that maps x to space of dimension l
b = bias

kernel machines learn a decision function regarding kernel values between training instances, $\{x_i\}_{i=1}^N$ dan test instance x as follows $f(x) = \sum_{i=1}^{N} \alpha_i k(x_i, x) + b$. Commonly, kernel function used is linear kernel $\varphi(x) = K(x, x') = x^T x$ and Kernel *Polynomial* $\varphi(x) = K(x, x') = ((x^T x) + 1)^d$. x and x' 'are pairs of two training data. Parameter $d > 0$ is a constant [15]. Which kernel function should be used for dot product substitution in feature space is highly dependent on data because this kernel function will determine the new features in which the separator function will be searched [16].

2.3. General Regression Neural Network

General Regression Neural Network (GRNN) is one network model radial basis which is often used to approach a function. The basis of the GRNN operation is essentially based on nonlinear regression (kernel) where the estimation of the expected output value is determined by the set of its inputs [17]. Although GRNN produces a multivariate vector output, with no prejudice to the description of the GRNN operating logic in this section it ,is simplified for the case of univariate output only [18].

$$E[y|x] = \frac{\int_{-\infty}^{\infty} y f(X,y) dy}{\int_{-\infty}^{\infty} f(X,y) dy} \tag{3}$$

In this case, y is the output predicted by GRNN, whereas X is the input vector $(x_1, x_2, ... , x_p)$ consisting of p predictor variable. $E[y|x]$ is the expected value of the output y given the input

vector *X* and *f(X,y)* is the joint probability density function of *X* and *y*. To justify the accuracy, we using Mean Absolute Percent Error (MAPE) which is smaller MAPE amount indicates that the model used for forecasting is gives more accurate with the (4):

$$MAPE = \frac{\sum_{t=1}^{n} |(\frac{X_t - F_t}{Xt})x100\%|}{n}$$ (4)

with,

X_t : Actual data at period-*t*
F_t : Prediction data at period-*t*
n   : Number of observation
t   : Period to *1,2,3,...,t*

classification of percentage to justify the accuracy can be seen in Table 1.

Table 1. MAPE Interpretation

MAPE	Interpretation
<4.9%	Highly Accurate Forecasting
5%-9.9%	Accurate Forecasting
10%-14.9%	Good Forecasting
15%-19.9%	Reasonable Forecasting
>20%	Inaccurate Forecasting

3. Analysis
3.1. Climate Analysis and Pre-modeling

Manado is the capital of North Sulawesi can be seen in Figure 1 which province with a tropical climate located in the Northern Hemisphere. Monsoon winds that blow periodically for two times per year become one of the leading factors that cause fluctuations in the amount of rainfall in each month. West monsoon (Asian monsoon) blows from October to March when the sun's pseudo position is in the Southern Hemisphere. This condition causes high air pressure in the Asian region and low pressure in Australia causes winds blowing from the Asian continent to the Australian continent. In the process of western monsoon passing through the Indian Ocean that has a lot of water vapor supply, thus causing the territory of Indonesia to receive additional water vapor that causes the month of October to March has greater rainfall potential or in general the territory of Indonesia, including Manado rainy season. Then the east monsoon (Australian monsoon) blows from April to September when the sun's pseudo position is in the Northern Hemisphere. This condition causes high air pressure in Australian territory, and low pressure in Asia causes winds blowing from the Australian continent to the Asian continent. In the process of tracing the East monsoon through the dried or desert strands of the Australian Ocean that cause the Indonesia region, including Manado to receive dry air, creating the low rainfall potential which in general the part of Indonesia is experiencing the dry season.

Figure 1. Manado, Indonesia

Figure 2 and Figure 3 explain the average rainfall of 30 years (1981-2010). Rain patterns in the Manado region could be distinguished between the rainy season and the dry season. Distribution of monthly rainfall U-shaped, the maximum amount of rainfall occurs in December-January-February (DJF). When the monsoon west of the amount of rain abundant, on the contrary when the eastern monsoon the amount of rainfall is minimal, while the minimum amount of rainfall occurs in June-July-August (JJA). In climatological science. It needs to be analyzed at 30 years because of the time span of the year has covered various global, regional and local phenomena (land breeze, monsoon wind, and El Nino–Southern Oscillation, Madden Julian Oscillation, and Pacific Decadal Oscillation, dipole mode). At the same time, rainfall trends to be caused by a particular factor (e.g., only an average of 5 years may be in one of those years there is a significant El-Nino phenomenon, so the average value becomes low):
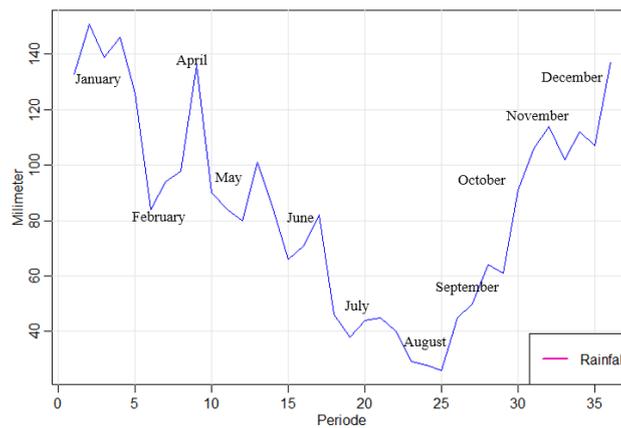
Figure 2. Rainfall 1980-2010 (30 years)
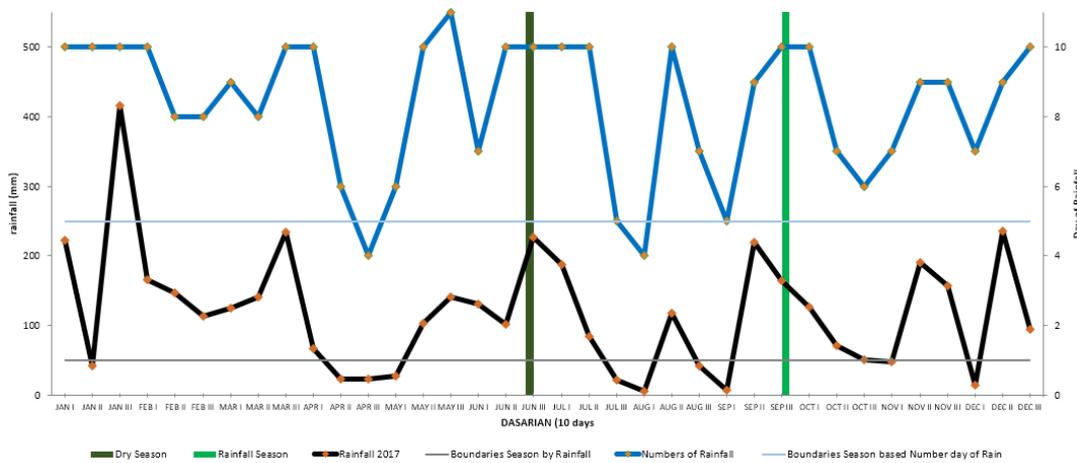
Figure 3. Characteristics of rainfall in Manado, Northern Sulawesi 1980-2010 (30 years)

Weather and global climate are a unified whole. The interaction between the atmosphere and the ocean will form a system that affects the weather and climate in Indonesia. Sub-surface monitoring results the global temperature in Figure 4 shows that the anomaly in the equatorial Pacific is still cold with a value close to zero. The warming of sea surface temperature (SST) around the waters of North Sulawesi has an impact on increasing the supply of water vapor as a material for the formation of rain clouds. The Northern SST anomaly is not warmer than the southern part of North Sulawesi province although both areas are positive.
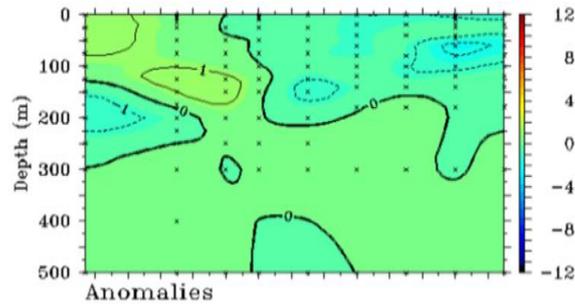
Figure 4. SST Anomalies in Northern Sulawesi

3.2. Neuro Computing

Numbers of techniques are used in climatological analysis such as copula used for pattern analysis of El Nino and La Nina [6, 19]. Application of short memory and long memory method for rainfall prediction and temperature [20] using of spline method, wavelet, and traditional time series. More popular in 20 years is the development of machine learning methods[21] such as a neural network, support vector machine, support vector regression. In this paper, we will use some of these methods to see the performance comparison of each model. After analyzing pre-modeling, the goal researchers to get the full picture of the information before building the model. This activity is essential to do because before creating the model it would be better to know what the phenomenon happened. In time series modeling, data now influenced by past data so that in this case the input data on the neural network. However FFNN [22] and GRNN using lag identification as an input component which is based on lags that have the most significant PACF value. However, this is due to the characteristics of Neural network model has in common with AR model. Based on the identification of the lag that can be seen in Figure 5. There are 3 lags significant which will be used as the component of data input, namely lag 2, 4, and 8 or it can be said that X_t is influenced by $X_{t-2}, X_{t-4}, X_{t-8}$.
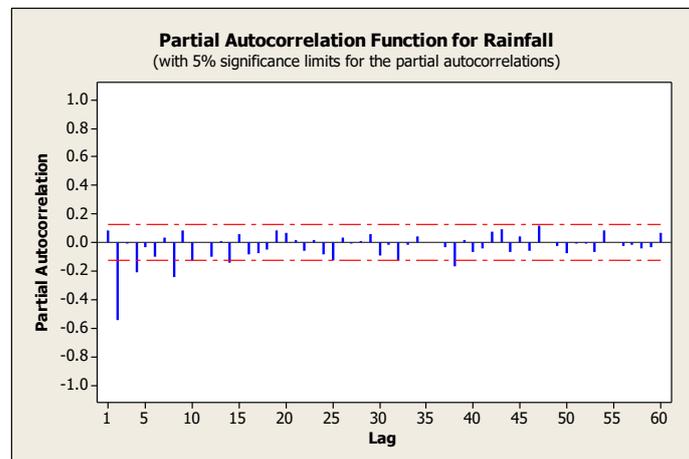
Figure 5. PACF rainfall

3.2.1. GRNN

The application of the General Regression Neural Network in forecasting consists of two stages: the training stage and the testing phase. GRNN network consists of four layers of processing units: the input layer, the pattern layer, the summation layer and the output layer. In the input layer consists of 3 units of neurons representing data return and 1 unit of input bias (b). 1 unit of input bias then passes data to the pattern layer with the input weight

whose value is equal to the data from the input neuron, it will be repeated continuously until all data in the input neuron is sent completely to pattern neurons. At the same time, 1 unit of biased neurons also passes data to the pattern layer with the name of the input bias weight equal to *1/spread*. Also, it will be repeated until all the data in the neuron bias is entirely sent to the pattern neuron. This illustration can be seen in Figure 6. The number of input bias weights is equal to the input data rainfall 241. The spread value is the radial function with the standard value = 1. The pattern layer consists of 241 neurons formed in the GRNN network training process. Each neuron of the pattern layer learns by finding the distance between the input weights data (D_i), then searches for the value of θ_i where θ_i in GRNN modeling using matlab is a basic radial activation function by obtaining input from the distance between data by obtaining input from the distance between input weight data and input bias $\theta_i = e^{-(X-U_i)'(X-U_i)/2\sigma^2}$. Furthermore, we obtained by GRNN to forecasting rainfall from the optimum weight of the training result. The GRNN model can be written as follows:

$$\hat{Y}(t) = \frac{S_W}{S_S} = \frac{\sum_{i=1}^{241} W_i \times \theta_i}{\sum_{i=1}^{241} \theta_i} = \frac{\sum_{i=1}^{241} W_i \times e^{-(b\sqrt{(X_{t-2}-X_{t-i}i)^2+(X_{t-4}-X_{t-4}i)^2+(X_{t-8}-X_{t-8}i)^2}}}{\sum_{i=1}^{241} e^{-(b\sqrt{(X_{t-2}-X_{t-i}i)^2+(X_{t-4}-X_{t-2}i)^2+(X_{t-8}-X_{t-12}i)^2}}}$$
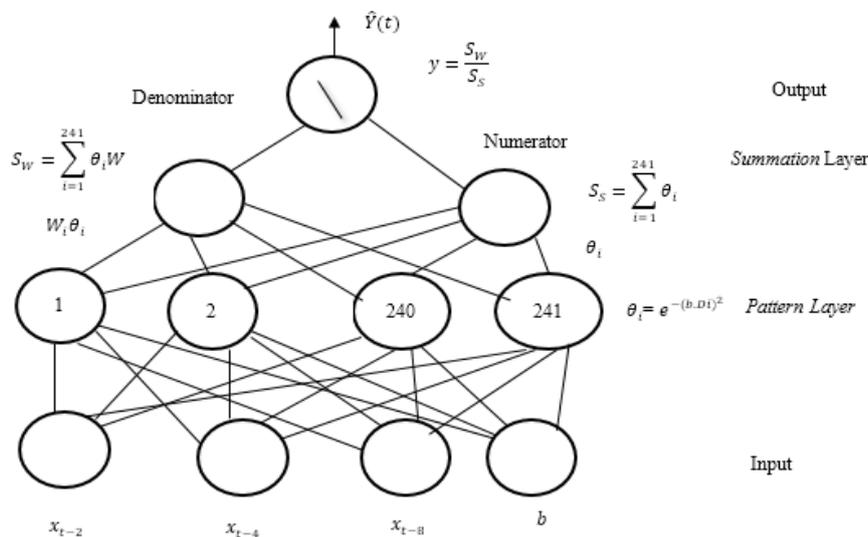
Figure 6. Architecture rainfall GRNN

3.2.2. Feedforward Neural Network

The network architecture to be used in the FFNN model [23-24] is a multilayer network which consisting of input layer, a hidden layer, and output layer. In the determination of the number of units in the input layer, there is no standard provision. Likewise, with the number of units in the hidden layer and output layer. Therefore, the problem is limited to the number of hidden layer units equal to the number of units in the input layer [25]. However, the network architecture that is formed consists of 4 units of variable inputs that are considered influential, 1 hidden layer consisting of 4 neurons, 1 neuron at the output layer and bias. While the activation function used in the hidden layer to the output layer is the binary sigmoid (sigmoid logistics) and the activation function used for the output signal is the function of idensity (purelin). Based on the FFNN network architecture that has been formed then the number of weights or parameters to be estimated using genetic algorithm 25 units consisting of 16 weights of neuron to give input signal on *hidden layer* (w_{ij}), 4 bias weight for *hidden layer* (w_{bj}), 4 the weight of the neuron to produce the output *layer* (w_{jo}) and 1 bias weight for the *output layer* (w_{bo}) can be seen in Figure 7 and Table 2.

Table 2. Optimum Weight

Xt	w_{bj}		w_{ij}		w_{bo}	w_{jo}
$Xt-1$	0.658	0.20	0.9912	0.952		-0.132
$Xt-4$	-0.9768	0.181	0.084	0.4321	0.1799	0.896
$Xt-8$	-0.9928	0.012	0.431	0.725		0.784

$$\hat{X}_t = 0.1799 + \frac{-0.132}{1 + \exp(-(0.658 + 0.20X_{t-1} + 0.181X_{t-4} + 0.012X_{t-8}))}$$
$$+ \frac{0.8966}{1 + \exp(-(0.768 + 0.9912X_{t-1} + 0.084X_{t-4} + 0.9023X_{t-8}))}$$
$$+ \frac{0.784}{1 + \exp(-(-0.9928 + 0.012X_{t-1} + 0.431X_{t-4} + 0.725X_{t-8}))}$$
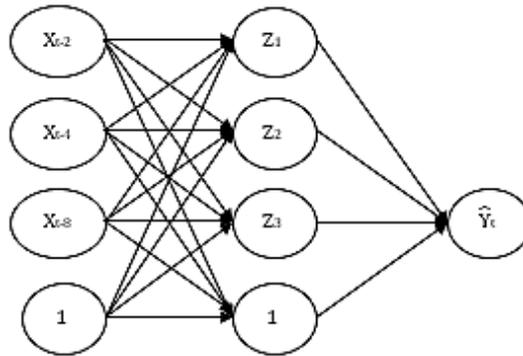
Figure 7. Architecture rainfall FFNN

3.2.3. Localized Multi Kernel Support Vector Regression

We extend SVR to LMKSVR. The idea of this localized kernel We can also apply the localized kernel idea to ϵ-tube SVR [26]. The decision function is rewritten as:

$$f(x) = \sum_{m=1}^{P} \eta_m(x|V)\langle w_m, \Phi_m(x^m)\rangle + b \tag{5}$$

moreover, the modified primal optimization problem is:

$$minimize \quad \frac{1}{2}\sum_{m=1}^{P}\|w_m\|_2^2 + C\sum_{i=1}^{N}(\xi_i^+ + \xi_i^-)$$

$$with\ respect\ to \quad w_m \in \mathbb{R}^{S_m}, \xi^+ \in \mathbb{R}_+^N, \xi^- \in \mathbb{R}_+^N, V \in \mathbb{R}^{P\times(D_G+1)}, b \in \mathbb{R}$$

$$subject\ to \quad \epsilon + \xi_i^+ \geq y_i - \sum_{m=1}^{P}\eta_m(x_i|V)\langle w_m, \Phi_m(x_i^m)\rangle - b \quad \forall i$$

$$\epsilon + \xi_i^- \geq \sum_{m=1}^{P}\eta_m(x_i|V)\langle w_m, \Phi_m(x_i^m)\rangle + b - y_i \quad \forall i$$

where $\{\xi^+, \xi^-\}$ are the vectors of slack variables and ϵ is the width of the regression tube. For a given V, the corresponding dual formulation is:

$$maximize\ J(V) = \sum_{i=1}^{N}y_i(\alpha_i^+ - \alpha_i^-) - \epsilon\sum_{i=1}^{N}(\alpha_i^+ + \alpha_i^-)$$

$$-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i^+ - \alpha_i^-)(\alpha_j^+ - \alpha_j^-)k_\eta(x_i, x_j)$$

$$with\ respect\ to \quad \alpha^+ \in \mathbb{R}_+^N, \alpha^- \in \mathbb{R}_+^N$$

$$subject\ to \quad \sum_{i=1}^{N}(\alpha_i^+ - \alpha_i^-) = 0$$

$$C \geq \alpha_i^+ \geq 0 \quad \forall i$$
$$C \geq \alpha_i^- \geq 0 \quad \forall i$$

and the resulting decision function is

$$f(x) = \sum_{i=1}^N (\alpha_i^+ - \alpha_i^-) k_\eta (x_i, x) + b. \tag{6}$$

to predict with LMKSVR first, we must determine the parameter value of C and epsilon by two kernels. In this research we use two type of kernel at the same time we proposed grid algorithm combined with cross-validation. Which is the leave-one-out method in training data. Furthermore, we were using the experimental cost 0.1,1,10,100 while the epsilon value of the experiment. So, the results obtained in Table 3.

       From Table 3 we get the best C and epsilon values by looking at the smallest error value of Grid Search cross-validation process. Cross-Validation used in default R program which Leave One out (LOO) so that the best parameter value is C=1 and epsilon=0.1. After the best parameters are determined then the value of C and epsilon used to map training data to feature space using linear kernel functions $\boldsymbol{\varphi}(\boldsymbol{x}) = \boldsymbol{K}(x, x') = \boldsymbol{x^T x}$ and radial basis $\varphi : \boldsymbol{x} \rightarrow \varphi(\boldsymbol{x})$ $\mathrm{K_{RBF}}(\mathrm{x}, \mathrm{x}') = \exp[-\frac{1}{2} \|\mathrm{x} - \mathrm{x}'\|^2$. So, we get the kernel equation as above calculation and then used for mapping data of higher dimension training. To get the values from the parameters $\boldsymbol{w}$ and b, use the Quadratic Programming Function. After the values of α and α* are obtained, the w value is calculated by $\boldsymbol{w} = \sum_{i=1}^l (\alpha_i - \alpha_i^*) \varphi(\boldsymbol{x_i})$. Moreover, the parameter values b or bias formed is the optimal value of the calculation as follows: $b = y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x_i})$ for linear and $b = y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x}) \mathrm{K_{RBF}}(\mathrm{x}, \mathrm{x}')$. So, by entering the value yi, w, $\varphi(\boldsymbol{x_i})$ and ε we obtained the parameter value b for hyperplane with linear kernel and radial basis function is: b=-0.000192. The results of w and bias values are as Table 4.

Table 3. Grid Search–Cross Validation

	cost	epsilon	Error
1	0.1	0.1	90.183
2	**1**	**0.1**	**52.666**
3	10	0.1	59.474
4	100	0.1	61.335
5	0.1	0.01	74.926
6	1	0.01	60.431
7	10	0.01	54.650
8	100	0.01	55.447
9	0.1	0.001	88.619
10	1	0.001	68.121
11	10	0.001	66.922
12	100	0.001	66.991
13	0.1	0.0001	82.112
14	1	0.0001	69.888
15	10	0.0001	68.458
16	100	0.0001	78.780

Table 4. *W* and Bias

Variable	W	B
x2	0.8727	
x4	0.00183	0.000192
x8	0.000065	

       From Table 4 it can be seen that the value of beta and w will be used in finding support vector, the resulting support vector will be used to predict using the SVR equation that is formed. Based on the results in Table 3 and Table 4 can be seen the data value of rainfall which is a support vector is 241 data, the data is inserted into the hyperplane equation so that the optimal model generated as follows:

$$f(\boldsymbol{x}) = \sum_{i=1}^l \beta_i \varphi^T(\boldsymbol{x_i}) \mathrm{K_{Linear}} \mathrm{K_{RBF}} + b$$
$$= (0.8727 \quad 0.00183 \quad 0.000065) \begin{pmatrix} x2 \\ x4 \\ x8 \end{pmatrix} + 0.000192$$

$$f(\boldsymbol{x}) = (0.8727 \ (x2) + 0.00183(x4) + 0.000065(x8)) + 0.00192$$

the result of the equation f (x) above for subsequent use in training and testing data as a predictor for subsequent use to find the error by using MAPE.

3.2.4. Comparing Models
There are rates of rainfall based on BMKG, Indonesia [27, 28]. First, Moderate rain, 20-50 mm per day. Second, Heavy rain, 50-100 mm per day, and third violent rain, above 100 mm per day. After performed forecasting, we compare with actual data in February 2018 can be seen in Figure 8. Soft computing by using feed forward neural network, general regression neural network, and localized multi-kernel support vector regression obtained that the average value of rainfall in Manado is 11.68 mm so that the general level of rain on that month is low. However, on a specific day rainfall in Manado reaches 45.1 mm. After getting the best model then compare between FFNN, GRNN, and LMKSVR Kernel Linear and Kernel Radial Basis. From Table 5 we can see that all of neurocomputing models FFNN, GRNN as well as LMKLSVR give highly accurate forecasting by justified MAPE and RMSE. At the same time, our best model is Localized Multi Kernel Support Vector Regression.

Table 5. Accuracy

Model	MAPE	RMSE	Category
FFNN	1.65%	8.54	Highly Acurate Forecasting
GRNN	2.65%	14.93	Highly Acurate Forecasting
LMKSVR	0.28%	4.756	Highly Acurate Forecasting
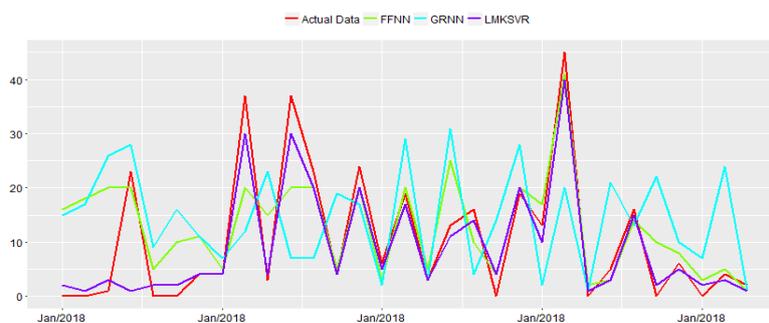
Figure 8. Comparing models

4. Conclusion
Rainfall data has a considerable variation compared to other climatic elements, both variations by place or time. Rainfall data is usually stored in one day and continuous. By knowing rainfall data, we can make observations in an area for development in agriculture and plantation as well as other fields. Also, it can also be used to determine the potential of an area against natural disasters caused by rain factors. However, based on the comparison by using neurocomputing, it is found that the results of the forecast method using FFNN, GRNN, and LMKSVR give highly accurate forecasting.

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